Table 19 Summary of supervised ML-based QoS/QoE correlation models

Ref.	ML Technique	Application *(approach)*	Dataset *(availability)*	Features	Output	Evaluation: Settings	Evaluation: Results[ab]
Khan et al. [235, 236]	ANFIS	Impact of network and application-level QoS on MPEG4 video streaming over wireless mobile networks *(NR regression)*	Simulations with Evalvid and *ns* − 2 · MPEG4 video source · 3 video types · variable network conditions · mobile video streaming client · PSNR-generated MOS	Video type Application-related: frame rate, send bitrate network-level: link bandwidth, packet error rate	MOS	Number of features= 5 5-layer ANFIS-NN: fuzzy layer, product layer, normalized layer, defuzzy layer, total output layer	For slight/gentle/rapid motion video type: · RMSE= 0.15/0.18/0.56 · $R^2 = 0.7/0.8/0.75$ *(on normalized data)* Outperformed by a simple regression model [235]
Machado et al. [287]	MLP-NN	Impact of QoS and video features over QoE *(FR/NR regression)*	Simulations on Evalvid integrated to *NS* − 2 ·3 video types (slight, gentle, rapid motion) ·565 data points · MOS, PSNR, SSIM and VQM generated by Evalvid and the VQMT tool	Delay, jitter, total/I/P/B frame loss · not clear if type of video is considered	A model is created for each output · MOS · PSNR · SSIM · VQM	Number of features= $6 \sim 7$ (-,10,1) MOS-MLP (-,10,1) PSN-MLP (-,12,24,1) SSIM-MLP (-,10,1) VQM-MLP	MOS-MLP · MSE≈ 0.01 PSNR-MLP · MSE≈ 0.14 SSIM-MLP · MSE≈ 0.01 VQM-MLPMSE · MSE≈ 0.3 *(on normalized data)*
Mushtaq et al. [328]	DT, RF, NB, SVM, *k*-NN, and NN	Impact of QoS, video features and viewer features over QoE *(NR classification)*	Collected from streaming videos over QoS-controlled emulated network, and MOS collected from a panel of viewers	network-level: · delay, jitter, packet loss, etc. application-related: · resolution type of video: · motion complexity viewer-related: · gender, interest, etc.	MOS	Number of features= 9 *k*-NN ($k = 4$) Other settings *(N/A)*	RF · MAE= 0.136 · TP= 74.8% DT · MAE= 0.126 · TP= 74% NB · MAE≈ 0.23 · TP≈ 57% SVM · MAE= 0.26 · TP≈ 61% 4-NN · MAE≈ 0.2 · TP= 49% NN · MAE≈ 0.18 · TP≈ 65% *(on normalized data)*

Table 19 Summary of supervised ML-based QoS/QoE correlation models *(Continued)*

Ref.	ML Technique	Application *(approach)*	Dataset *(availability)*	Features	Output	Evaluation Settings	Evaluation Results[ab]
MLQoE [89]	SVR, MLP-NN, DT, and GNB	modular user-centric correlation of QoE and network QoS metrics for VoIP services *(NR regression)*	3 datasets of VoIP sessions under different network conditions generated with OMNET++: during handover (dataset 1), in a network with heavy UDP traffic (dataset 2), in a network with heavy TCP traffic (dataset 3) QoE assessed with user-generated MOS and program-generated PESQ and E-model QoE	network-related: · delay, jitter, packet loss, etc.	MOS	Number of features= 10 MLP-NN $(10, 2 \sim 5, 1)$ Gaussian, linear, and polynomial kernel SVR	SVR · $MAE_1 = 0.66$ · $MAE_2 = 0.65$ · $MAE_3 = 0.47$ MLP-NN · $MAE_1 = 0.75$ · $MAE_2 = 0.68$ · $MAE_3 = 0.53$ DT · $MAE_1 = 0.73$ · $MAE_2 = 0.55$ · $MAE_3 = 0.5$ GNB · $MAE_1 = 0.69$ · $MAE_2 = 0.68$ · $MAE_3 = 0.53$ *(on normalized data)*
Dermibilek et al. [114]	RF, BG, and DNN	Correlation of QoE and network and application QoS metrics for video streaming services *(NR regression)*	INRS dataset, including user-generated MOS on audiovisual sequences encoded and transmitted with varying video and network parameters, and other pub *(public [112])*	network-related: delay, jitter, packet loss, etc. application-related: video frame rates, quantization parameters, filters, etc.	MOS	Number of features: ·RF_1, $BG_1 = 34$ ·RF_2, $BG_2 = 5$ ·DNN_{21}, $DNN_{22} = 5$ RF, BG tree size= 200 Number of hidden layers: ·$DNN_{21} = 1$ · DNN_{22} hidden= 20	RF_1 · RMSE= 0.340 · PCC= 0.930 RF_2 · RMSE= 0.340 · PCC= 0.930 BG_1 · RMSE= 0.345 · PCC= 0.928 BG_2 · RMSE= 0.355 · PCC= 0.925 DNN_{21} · RMSE= 0.403 · PCC= 0.909 DNN_{22} · RMSE= 0.437 · PCC= 0.894 *(on normalized data)*

[a] Average values. Results vary according to experimental settings
[b] Accuracy metrics: mean square error (MSE), mean absolute error (MAE), root MSE (RMSE), correlation coefficient (R), Pearson correlation coefficient (PCC)

Table 20 Summary of ML-based QoS/QoE prediction models for HAS and DASH

Ref.	ML Technique *(training)*	Application *(approach)*	Dataset *(availability)*	Features	Output	Evaluation Settings	Evaluation Results[ab]
CS2P [432]	Supervised: HMM *(offline)*	Throughput prediction for midstream bitrate adaptation in HAS clients to improve the QoE for video streaming *(regression)*	iQIYI dataset consisting of 20 million sessions covering ·3 million unique clients IPs and ·18 server IPs ·87 ISPs	Throughput samples	Throughput 1 $\sim$ 10 periods ahead	HMM model per cluster of similar sessions: · Number of states= 6 · Number of samples= 100 SVM, GBR single model for all sessions: · Number of features=6	MAE= 7% *(on normalized data)* · up to 50% more accurate than SVR, GBR and HMM with no clustering · 3.2% improvement on overall QoE · 10.9% improved bitrate over MPC
Claeys et al. [102]	Reinforcement learning: Q-Learning *(online)*	Video quality adaptation in a HAS client to maximize QoE under varying network conditions *(rule extraction)*	ns-3 simulation based on TCP streaming sessions in Norway's Telenor 3G/HSDPA mobile wireless network dataset. *(public [384])*	State: · client buffer filling level · client throughput level Reward: QoE as function of · targeted quality level · span between current and targeted video quality level · rebuffering level	Finite action set of $N = 7$ possible video quality levels (sotmax selection)	Improvement compared to Microsoft MSS: ·9.12% higher estimated MOS ·16.65% lower standard deviation	$\cdot S = (N+1)\frac{B_{max}}{T_{seg}+1}$ $\cdot A = N$

[a]Average values. Results vary according to experimental settings
[b]Evaluation metrics: mean absolute error (MAE); *S*: number of state variables; *A*: number of possible actions per state